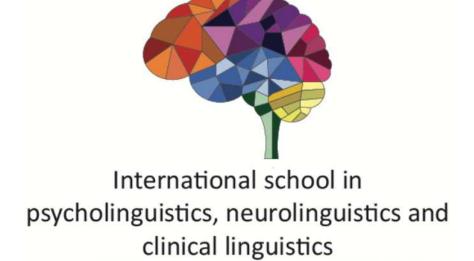
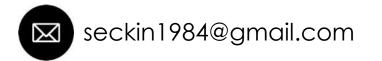
Hitchhikers' guide to mixed effects regression models Logistic ME regression

GLMER



Dr. Seçkin Arslan









This lecture

This lecture:

- (i) Generalized linear mixed-effects regression (glmer)
- (ii) Example with accuracy data





This lecture

When we fit a linear regression model, we always assume the response has a continuous scale (e.g. response times)



What if we analyse ordinary response on 1-5 scale?





We cannot use linear Imm models for binary variables 1-0 This is more of a classification problem.



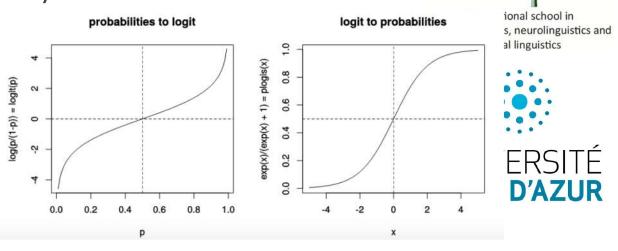
Generalized linear (mixed-effects) regression = GLM(ER)

is a generalization of linear regression

Logistic regression = dependent variable is binary (1 = accurate, 0 = inaccurate)

Logistic regression converts binary data into continuous data

"log odds link" function.



- We will use glmer (generalized mixed-effects regression) to analyse proportions of looks
 - Logistic regression automatically transforms binary data with log odds link function log(p / (1-p))
 - this represents probability in a form of continuous value.
 - Probability in this case is whether participants looks at target (1) or non-target (0).





- ► Logistic mixed-effects regression assumes
 - Relationship between dependent variable and independent variable is linear.
 - ► Multicollinearity is not strong
 - ► And there are no assumptions about normality of distribution of residuals.





► How to import your data into R

COGNITIVE NEUROPSYCHOLOGY, 2017 https://doi.org/10.1080/02643294.2017.1394284







Predicting the sources of impaired wh-question comprehension in non-fluent aphasia: A cross-linguistic machine learning study on Turkish and German

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ABSTRACT

This study investigates the comprehension of wh-questions in individuals with aphasia (IWA) speaking Turkish, a non-wh-movement language, and German, a wh-movement language. We examined six German-speaking and 11 Turkish-speaking IWA using picture-pointing tasks. Findings from our experiments show that the Turkish IWA responded more accurately to both object who and object which questions than to subject questions, while the German IWA performed better for subject which questions than in all other conditions. Using random forest models, a machine learning technique used in tree-structured classification, on the individual data revealed that both the Turkish and German IWA's response accuracy is largely predicted by the presence of overt and unambiguous case marking. We discuss our results with regard to different theoretical approaches to the comprehension of wh-questions in aphasia.

ARTICLE HISTORY

Received 26 January 2017 Revised 28 July 2017 Accepted 13 October 2017

KEYWORDS

Non-fluent aphasia; random forest algorithm; sentence comprehension; wh-in-situ; wh-questions; wh-movement

The data is from this paper, you can read if you are interested.





► Follow from Rstudio Cloud (Recommended)

https://rstudio.cloud/



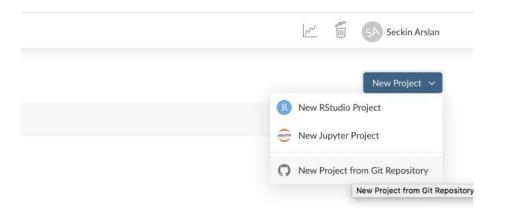


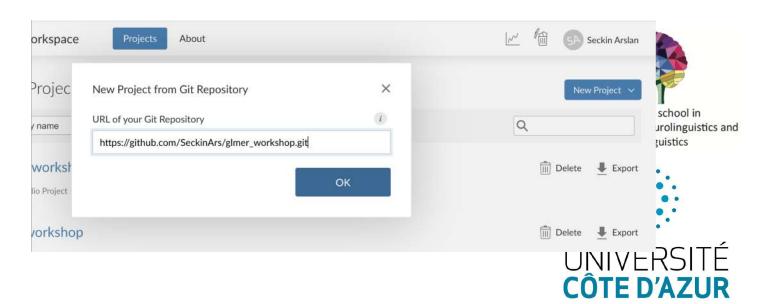


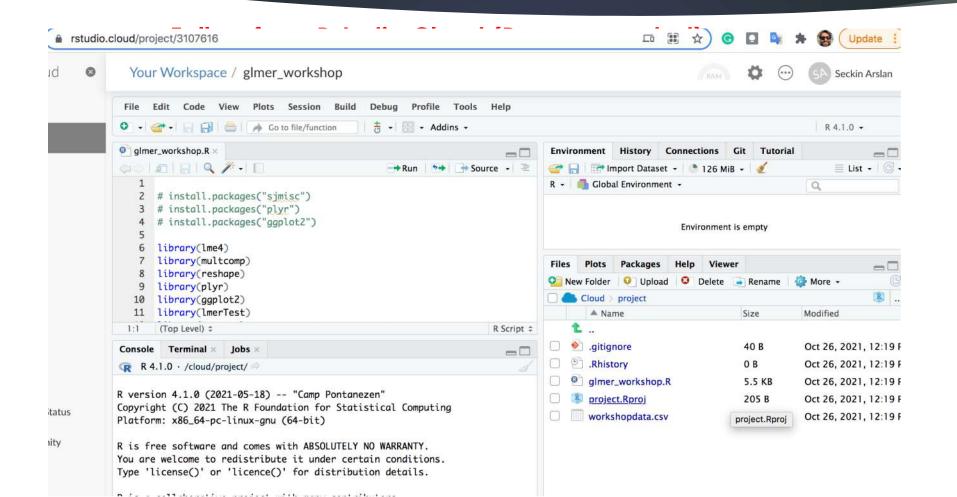
Follow from Rstudio Cloud (Recommended)

https://rstudio.cloud/

https://github.com/SeckinArs/glmer_workshop.git



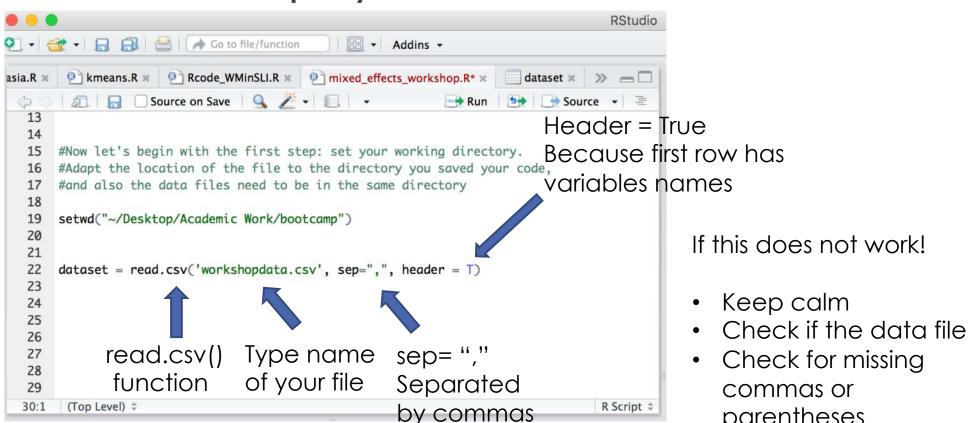








How to import your data into R

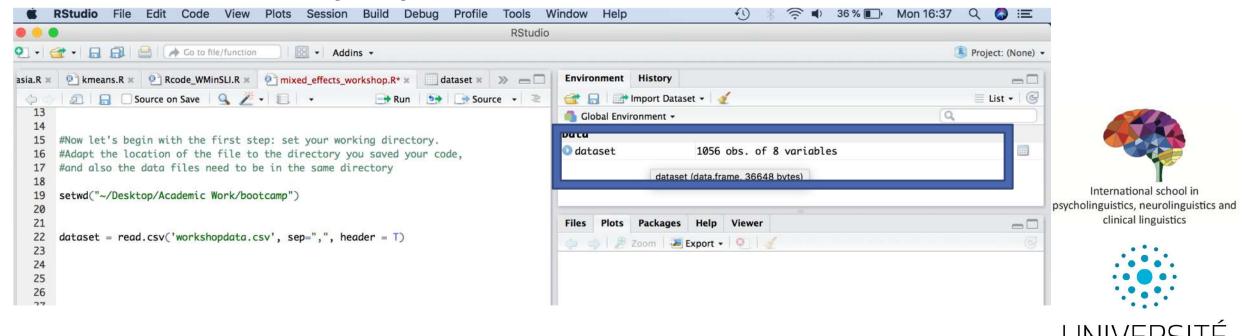






parentheses

► How to import your data into R

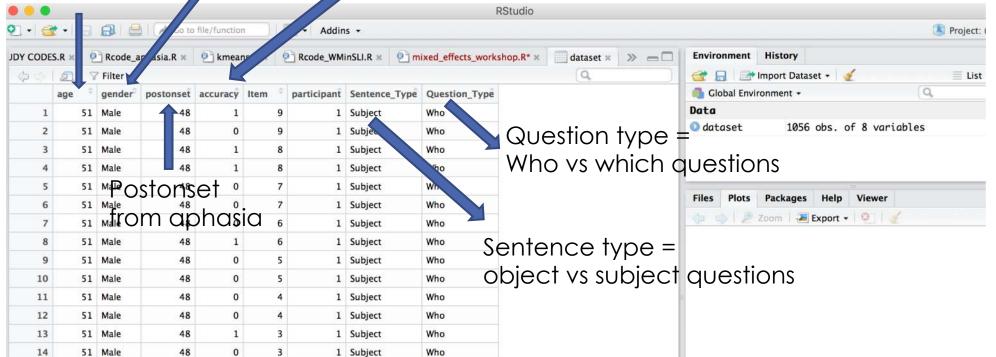


CÔTE D'AZUR



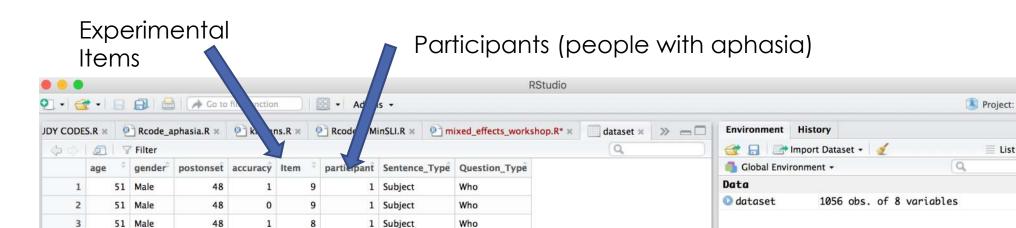
1 Subject

15









Who

1 Subject

7

7

6

3

3

51 Male

5

6

7

8

9

10

11

12

13

14

15

48

48

48

48

48

48

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48

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Plots Packages Help Viewer

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To get an idea about the data,

Run str() function





To get an idea about the data,

Run summary() function

> summary(dataset)

age	gender	postonset	accuracy	Item	participant
Min. :51.00	Female:192	Min. : 1.00	Min. :0.0000	Min. : 1.00	Min. : 1
1st Qu.:56.00	Male :864	1st Qu.: 1.00	1st Qu.:0.0000	1st Qu.: 3.75	1st Qu.: 3
Median :63.00		Median : 11.00	Median :1.0000	Median: 6.50	Median: 6
Mean :62.82		Mean : 27.73	Mean :0.5881	Mean : 6.50	Mean : 6
3rd Qu.:69.00		3rd Qu.: 22.00	3rd Qu.:1.0000	3rd Qu.: 9.25	3rd Qu.: 9
Max. :74.00		Max. :180.00	Max. :1.0000	Max. :12.00	Max. :11

Sentence_Type Question_Type

Object:528 Which:528 Subject:528 Who:528





To get an idea about the data,

Run head() function

> head(dataset)

	age	gender	postonset	accuracy	Item	participant	Sentence_Type	Question_Type
1	51	Male	48	1	9	1	Subject	Who
2	51	Male	48	0	9	1	Subject	Who
3	51	Male	48	1	8	1	Subject	Who
4	51	Male	48	1	8	1	Subject	Who
5	51	Male	48	0	7	1	Subject	Who
6	51	Male	48	0	7	1	Subject	Who



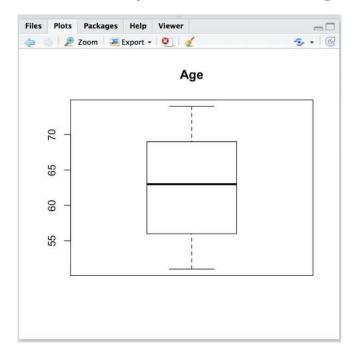


```
boxplot()
hist()
qqnorm() & qqline()
plot()
barplot()
```





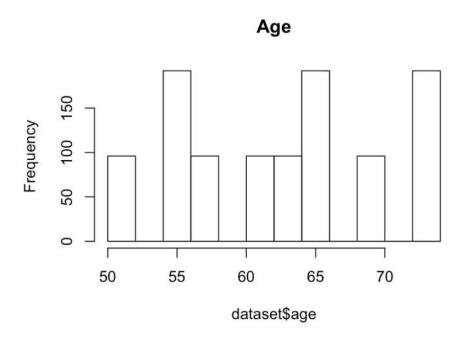
boxplot(dataset\$age, main = "Age")







hist(dataset\$age, main = "Age")



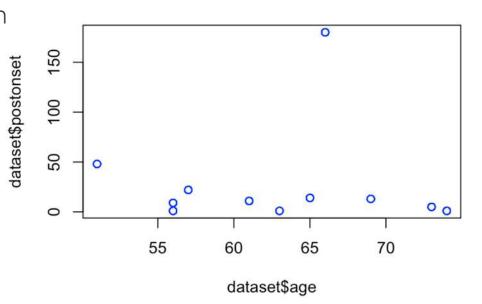




plot(dataset\$age, dataset\$postonset, col="blue")

This will return a simple scatter plot with

Postonset and age

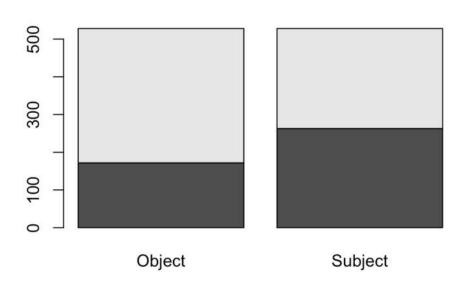






plot.table = table (dataset\$accuracy, dataset\$Sentence_Type)

barplot (plot.table)







Visualisation: ggplot

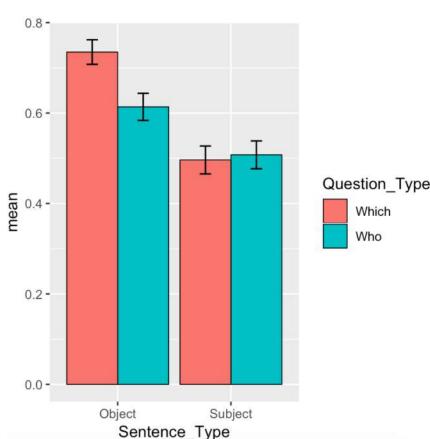
▶ A quick peek into the data: visualize the data

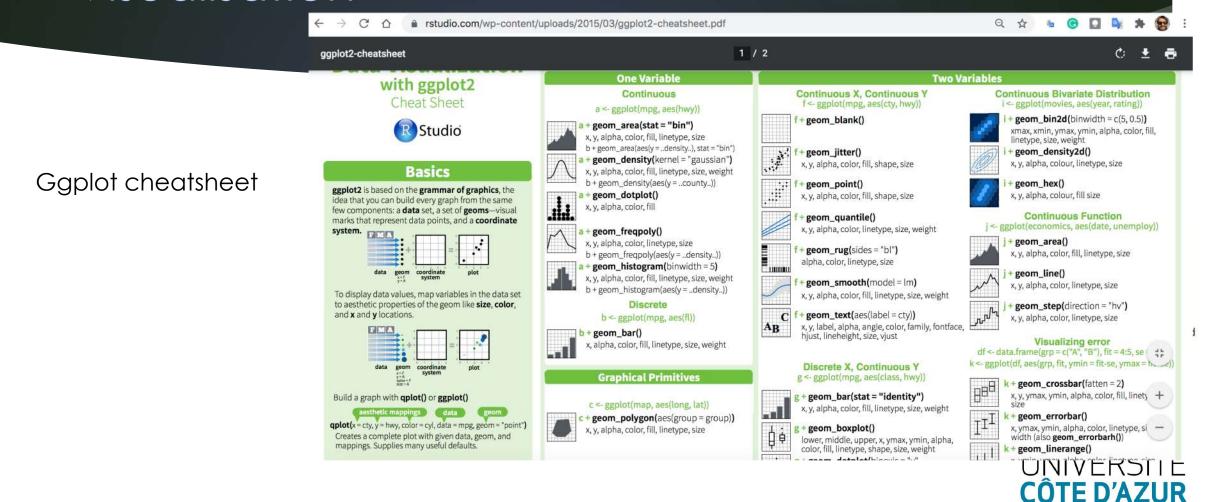




Visualisation: ggplot

▶ A quick peek into the data: visualize the data





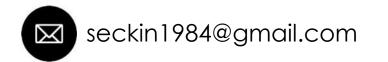
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Hitchhikers' guide to mixed effects regression models Logistic ME regression

4.1 Understanding mixed and fixed effects.



Dr. Seçkin Arslan









Running a generalized linear mixed-effect regression (glmer) model for accuracy data.

glmer (dependent var ~ independent var 1 * independent

var2.... + (1 | random intercept) + (1 | random intercept),

family = binomial, data = dataset))





Running a generalized linear mixed-effect regression (glmer) model for accuracy data.

► Simple random effect structure

Fixed-effects

model1 = glmer(accuracy ~ Sentence_Type * Question_Type + (1 | Item),

family-binomial, data=dataset)

summary(model1)

Random effect





Hitchh **mixed effec**

Simple random effect structu

summary (model1

Output ---->

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [
almerMod]
 Family: binomial (logit)
Formula: accuracy ~ Sentence_Type * Question_Type + (1 | Item)
   Data: dataset
    AIC
             BIC
                  logLik deviance df.resid
 1396.0
         1420.8
                   -693.0 1386.0
                                       1051
Scaled residuals:
   Min
            10 Median
                            30
                                   Max
-1.9957 -1.0301 0.5888 0.8454 1.1906
Random effects:
Groups Name
                   Variance Std.Dev.
 Item (Intercept) 0.04853 0.2203
Number of obs: 1056, groups: Item, 12
Fixed effects:
                                     Estimate Std. Error z value Pr(>|z|)
                                       1.0307
                                                 0.1540
                                                          6.692 2.21e-11 ***
(Intercept)
                                                 0.1871 -5.590 2.27e-08 ***
Sentence_TypeSubject
                                      -1.0460
Question_TypeWho
                                      -0.5626
                                                 0.1892 -2.974 0.00294 **
Sentence_TypeSubject:Question_TypeWho
                                      0.6086
                                                 0.2578
                                                         2.361 0.01825 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Correlation of Fixed Effects:
           (Intr) Snt_TS Qst_TW
Sntnc_TypSb -0.683
Qustn_TypWh -0.674 0.555
Sn+ TS · O TW 0 105 _0 725 _0 731
```

Simple random intercept with nested factors

Fixed-effects

model1 = glmer(accuracy ~ Sentence_Type * Question_Type + (1 | participant / gender), family=binomial, data=dataset)

summary(model1)

Gender as nested factor within subjects





Hitchhi **mixed effec**t

► Simple random interce

```
model1 = glmer(accura (1 | participant/gender),
```

summary(model1)

```
almerMod7
 Family: binomial (logit)
Formula: accuracy ~ Sentence_Type * Question_Type + (1 | participant/gender)
   Data: dataset
    AIC
             BIC
                   logLik deviance df.resid
 1292.8
          1322.6
                   -640.4 1280.8
                                       1050
Scaled residuals:
   Min
            10 Median
                            30
                                   Max
-3.6140 -0.8180 0.4352 0.7570 1.7272
Random effects:
                               Variance Std.Dev.
Groups
                   Name
gender:participant (Intercept) 0.08661 0.2943
participant
                   (Intercept) 0.58828 0.7670
Number of obs: 1056, groups: gender:participant, 11; participant, 11
Fixed effects:
                                     Estimate Std. Error z value Pr(>|z|)
(Intercept)
                                       1.1734
                                                  0.2893
                                                          4.056 4.98e-05 ***
Sentence_TypeSubject
                                      -1.1770
                                                  0.1991 -5.911 3.40e-09 ***
Ouestion_TypeWho
                                      -0.6269
                                                  0.1996 -3.140 0.00169 **
                                       0.6796
                                                  0.2737
                                                          2.483 0.01302 *
Sentence_TypeSubject:Question_TypeWho
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1
Correlation of Fixed Effects:
           (Intr) Snt_TS Qst_TW
Sntnc_TypSb -0.385
Qustn_TypWh -0.378 0.549
Snt_TS:Q_TW 0.276 -0.722 -0.730
```

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [

► Two independent random intercepts

Fixed-effects

model3 = glmer(accuracy ~ Sentence_Type * Question_Type + (1 | participant), family=binomial, data=dataset)

summary (model3)

Two independent random effects





Hitch mixed effe

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [
glmerMod]
Family: binomial (logit)
```

Formula: accuracy ~ Sentence_Type * Question_Type + (1 | Item) + (1 |

participant) Data: dataset

BIC logLik deviance df.resid AIC 1286.8 1316.6 -637.4 1274.8 1050

Scaled residuals:

Min 1Q Median 3Q Max -3.7514 -0.8095 0.4149 0.7509 1.9445 ► Two independent rc

Random effects:

```
Variance Std.Dev.
                          Groups
                                    Name
model3 = glmer(acc Item
                                    (Intercept) 0.08219 0.2867
                         participant (Intercept) 0.70366 0.8388
       (| | | tem) + (| Number of obs: 1056, groups: Item, 12; participant, 11
```

Fixed effects:

summary (model3)

```
Estimate Std. Error z value Pr(>|z|)
                                               0.3059 3.899 9.65e-05 ***
(Intercept)
                                     1.1927
                                               0.2009 -5.957 2.57e-09 ***
Sentence_TypeSubject
                                    -1.1965
Question_TypeWho
                                    -0.6372
                                               0.2012 -3.167 0.00154 **
Sentence_TypeSubject:Question_TypeWho 0.6907
                                               0.2758 2.504 0.01227 *
```

Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1

Correlation of Fixed Effects:

(Intr) Snt_TS Qst_TW

Sntnc_TypSb -0.368

Oustn TypWh -0.361 0.549

Fixed-effects

► Random slope

model4 = glmer(accuracy ~ Sentence_Type * Question_Type + (age_Item) + (1 | participant), family=binomial, data=dataset)

summary (model4)

Random slopes for age per item





Hitch mixed effe

```
Family: binomial (logit)
```

Formula: accuracy ~ Sentence_Type * Question_Type + (age | Item) + (1 |

participant) Data: dataset

glmerMod]

AIC BIC logLik deviance df.resid 1289.8 1329.5 -636.9 1273.8 1048

Random slope

summary(model4)

Min 1Q Median **3Q** Max -3.7401 -0.8085 0.4130 0.7509 1.8623

Random effects:

Scaled residuals:

Groups Name Variance Std.Dev. Corr model4 = glmer(acc Item

(Intercept) 1.0139156 1.00693

0.0001293 0.01137 -1.00 age

(□□□ | †⊕↑ participant (Intercept) 0.7084785 0.84171

Number of obs: 1056, groups: Item, 12; participant, 11 data=dataset)

Fixed effects:

(Intercept) 0.3071 3.899 9.67e-05 *** 1.1974

Sentence_TypeSubject -1.1990 0.2011 -5.962 2.49e-09 ***

Estimate Std. Error z value Pr(>|z|)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [

Question_TypeWho 0.2015 -3.171 0.00152 ** -0.6389

Sentence_TypeSubject:Question_TypeWho 0.6924 0.2761 2.508 0.01213 *

Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1

Correlation of Fixed Effects:

(Intr) Snt_TS Qst_TW

Sntnc_TypSb -0.367

► Adding a fixed-effect

Fixed-effects

```
model5 = glmer(accuracy ~ Sentence_Type * Question_Type + postonset +
```

(1 | Item) + (1 | participant), family=binamial

data=dataset)

Random slopes for age per item





summary (model5)

almerMod] Family: binomial (logit) Formula: accuracy ~ Sentence_Type * Question_Type + postonset + (1 | Item) + (1 | participant) Hitcl Data: dataset mixed effe AIC BIC logLik deviance df.resid 1286.9 1321.6 -636.5 1272.9 Scaled residuals: Min 1Q Median ► Adding a fixed-effe-3.7377 -0.8135 0.4142 0.7525 1.9214 Random effects: Name Variance Std.Dev. Groups model5 = glmer(acc Item (Intercept) 0.08189 0.2862 participant (Intercept) 0.58359 0.7639 postonset + Number of obs: 1056, groups: Item, 12; participant, 11 (1 | Item) + Fixed effects: data=dataset) Estimate Std. Error z value Pr(>|z|) (Intercept) Sentence_TypeSubject -1.196587 0.200882 -5.957 2.57e-09 *** -0.637187 0.201207 -3.167 0.00154 ** Question_TypeWho postonset -0.006901 0.004809 -1.435 0.15123 Sentence_TypeSubject:Question_TypeWho 0.690730 0.275826 2.504 0.01227 * summary(model5) Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1 Correlation of Fixed Effects: (Intr) Snt_TS Qst_TW pstnst

Sntnc_TypSb -0.360

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [

Fixed-effects

Adding a fixed-effect

model6 = glmer(accuracy ~ Sentence_Type * Question_Type + postonset +

(postonset | Item), family=binomial, data=dataset)

Random slopes for age per item





summary(model6)

Hitc mixed ef

Adding a fixed-ef

```
model6 = glmer(a
postonset +
```

(postons

summary(model6)

```
> summary(model6)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [
glmerMod]
Family: binomial (logit)
Formula: accuracy ~ Sentence_Type * Question_Type + postonset + (postonset |
   Item)
  Data: dataset
    AIC
             BIC
                  logLik deviance df.resid
          1418.5
 1378.8
                  -681.4 1362.8
                                     1048
Scaled residuals:
   Min
            10 Median
                           30
                                 Max
-2.1710 -1.0449 0.5558 0.8758 1.7656
Random effects:
Groups Name
                  Variance Std.Dev. Corr
       (Intercept) 4.882e-02 0.220949
Item
       postonset 6.867e-08 0.000262 1.00
Number of obs: 1056, groups: Item, 12
Fixed effects:
                                    Estimate Std. Error z value Pr(>|z|)
                                    1.221902 0.161690 7.557 4.12e-14 ***
(Intercept)
Sentence_TypeSubject
                                   Question_TypeWho
                                   -0.576685
                                              0.191617 -3.010 0.00262 **
postonset
                                   -0.006213
                                              0.001323 -4.694 2.67e-06 ***
                                              0.260887
                                                        2.391 0.01682 *
Sentence_TypeSubject:Question_TypeWho 0.623672
```

Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1

(Intr) Snt_TS Qst_TW pstnst

Correlation of Fixed Effects:

Additional consideration

When specifying the random effect structure we use (1 | Item)

Here 1 refers to the "intercept" - (1 | Item) is an intercept only model (i.e. slopes per item do not vary)

Alternatives:

(Age | Item) – slopes per item vary by age

(1 +Age | Item) – slopes per item vary by age plus the intercep

(0+Age | Item) – slopes per item vary by age we force to exclude intercept





- ▶ Which model do we choose?
- ▶ Prefer more parsimonious models
- Rule of thumb: "smaller the better" chose models with smaller AIC/BIC values
- ▶ Compare models:
- # anova(model1, model2)





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Hitchhikers' guide to mixed effects regression models Logistic ME regression

4.3. Interpreting logistic regression



Dr. Seçkin Arslan









► Interpreting logistic coefficients

```
#fixef(model1)
```

#plogis(fixef(model1) ["(Intercept)"])

= 0.7672304

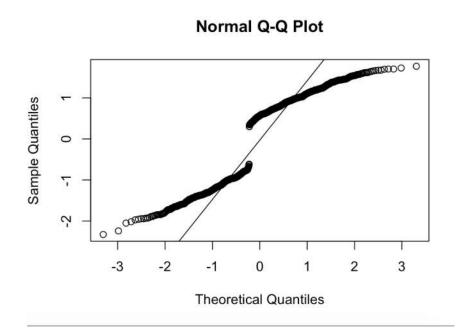
On average 76% chance of being correct

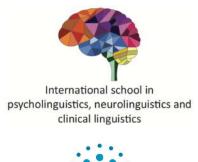




► Inspecting distribution of your residuals

```
# qqnorm (resid(model1))
# qqline (resid(model1))
```







Post-hoc tests with emmeans

emmeans(model4, "Question_Type", by = "Sentence_Type")

pairs(emmeans(model4, "Question_Type", by = "Sentence_Type")

```
> pairs(emmeans(model4, "Question_Type", by = "Sentence_Type"))
Sentence_Type = Object:
  contrast    estimate    SE    df    z.ratio    p.value
  Which - Who     0.6389    0.201    Inf     3.171     0.0015

Sentence_Type = Subject:
  contrast    estimate    SE     df    z.ratio    p.value
  Which - Who     -0.0536    0.189    Inf     -0.284     0.7763

Results are given on the log odds ratio (not the response) scale.
```





Alternative post-hocs

#first subset your data into different question types

data.who <- subset(dataset, Question_Type == 'Who')
data.which <- subset(dataset, Question_Type == 'Which')</pre>





library(multcomp) #Install.package("multcomp") first if you don't have this package

summary(glht(model,linfct=mcp(Factor = "Tukey")))

```
# data.who$Factor = interaction(data.who$Sentence_Type)

# model = glmer(accuracy ~ Factor + (1 | Item) + (1 | participant) sycholinguistics, neurolinguistics, neurolinguistics and data=data.who, family = binomial)

# summary(model)
```

Linear Hypotheses:



Great subject – object sentences in who questions are different...





How should you report a logistic mixed-effects regression model? A best way is to provide a table

Fixed effects:

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1





How should you report a logistic mixed-effects regression model?

"outputs from a generalized logistic mixed-effects regression model have shown significant effects of Question Type and Sentence Type and of interactions between the two." (see table X). s





Hitchhikers' mixed effects reg

Results are given on the log odds ratio (not the response) scale.

How should you report a post-hoc test results

"A series of post-hoc tests confirmed that the subjects were more accurate in responding to "which questions" than "who questions" ($\beta = 0.63$, SE = 0.20, z = 3.17).



